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Longitudinal analysis of car ownership and car travel demand in the Paris region using a pseudo-panel data approach

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Abstract

We are interested in this paper to the longitudinal analysis of car ownership (number of cars per household) and car travel demand (the number of trips made by car per household and per day) in the Paris metropolitan area. The aim is to find the determinants of car ownership and use and the longitudinal analysis allow us to determine life-cycle and generation effects. Income and fuel price elasticities of demand for different residential areas and income groups are also determined. A pseudo panel data approach (which consists in grouping individuals or households into cohorts in using repeated cross-sectional data) is adopted using a succession of five large independent surveys (*Enquête Globale Transport*) conducted between 1976 and 2010. The cohorts of households are built from time-invariant variables. Concerning the modelling, we have estimated two models (for car ownership and car travel demand) having a semi-log linear specification. We find an elasticity of income on car ownership of 0.47. The influence of income on car ownership is decreasing with regards to a rise in income and is not significant for high income households. Moreover, the income is not a determinant of car ownership in the most urbanized area while it is positive in car dependent areas. The fuel price elasticity on car travel found is -0.22. Furthermore, the elasticity is more important in dense territories where the households can more easily adapt their behavior to a change in fuel price because alternative modes are available.

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Keywords: Car ownership; Car use; Pseudo panel; Longitudinal analysis; Paris region

1. Introduction

Longitudinal data offer the advantage to distinguish life-cycle and generation effects which is not possible with

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cross sectional data (one period). These data are also useful for long run income or price elasticities. For a longitudinal analysis, two sorts of data are commonly used: true panel data which follow the same individuals over time and time-series aggregate data constituted of relatively large groups of individuals aggregated generally at national or regional level. However these data have some constraints. Panel data are often not available over a long period of time while time-series aggregate data covers long periods of time but lack of individual information. An alternative is to create pseudo panel data constructed from repeated independent cross-sectional data which enable to follow groups of individuals changing over time but sharing time-invariant characteristics.

A longitudinal analysis of car ownership and car travel demand is proposed in the Paris region in order to identify their determinants and to question the 'Peak Car' hypothesis. We investigate in particular the influence of economic and geographical factors as well as the influence of life-cycle and of generations. Furthermore, the objective is to exhibit contrasted reactions of different categories of households over time in determining income and fuel price elasticities of demand distinguishing different residential locations and income groups. This approach enables also to interrogate the hypothesis of the saturation of demand and in particular the possible decoupling of car ownership and use from economic variables (income, fuel price). A pseudo panel data is created in the Paris metropolitan area using the 'Enquête Globale Transport' surveys from 1976 to 2010 to estimate car ownership and car travel demand with a semi-log model. In the next section, a literature review is presented focusing on the 'Peak Car' hypothesis and introducing the construction process of pseudo panel data and the applications in transport field. In section 3, the Parisian context of car ownership and travel is presented. Then, we set out the data and the modelling used in section 4. The estimation results are discussed in section 5.

2. Literature review

2.1. Peak Car

After several decades of car use growth, an inflection of travel behaviour is observed. Car use per head, and sometimes total car traffic, has slowed and tend to reach a threshold at the turn of the 2000s (Millard-Ball and Schipper, 2010; ITF, 2011). This phenomenon is observed in many developed countries at an aggregated level. Goodwin (2012) has expressed the different scenarios for the future of car use and among all the 'Peak Car' which is a hypothesis that the recent change in trend could be the early sign of a sustained decrease of individual car use. Recent research issues have tackled the possible multidimensional causes of this break in trend.

The slowing down of car traffic is influenced by the recent economic slowdown and in particular by the rise in fuel price in the 2000s. Gargett (2012) who has gathered longitudinal data for 25 countries explains this levelling off by real petrol prices and also by fluctuations in the economy and a saturating effect of time. If the response of households to the change in fuel price was generally weak during the period 1970s-1990s, it has tended to strengthen in the 2000s (Litman, 2013). Indeed, the reaction is stronger during a long period of rise (2004-2008) and of volatility (since 2008) (Collet, 2012; Hivert and Madre, 2012).

According to Metz (2010), the saturation of the demand for daily travel is due to the diminishing marginal utility of additional trips which tends to increase a reluctance to travel further. We can also mention the movement of re-densification which contribute to a reduction of car use since in dense areas people can more easily reach their destinations without automobile (Goodwin and Van Dender, 2013; Headicar, 2013; Buehler and Pucher, 2012). In France, politics promoting tramways have contributed to reduce car traffic in many cities in the 2000s (De Solère, 2012).

Another driver is the change in travel behaviour for new generations. Indeed, the percentage of young adults having a driving licence as well as the motorisation has decreased with regards to the previous generations in several developed countries (Sivak and Schoettle, 2012; Kuhnimhof et al., 2012; Delbosc and Currie, 2013).

Newman and Kenworthy (2011) have summarised series of possible causes of saturation: the growth in public transport infrastructures, the improvements in public transport supply or quality of service, the densification of city-centers and suburbs to the detriment of outer-urban areas in several metropolitan areas, the ageing of population in cities, the diffusion of an urban culture and the Marchetti constant (Marchetti, 1994).

In the case of our paper, we are interested in the 'Peak Car' hypothesis from the perspective of the change in trend for the new generations.

2.2. Pseudo panel data approach

For a longitudinal analysis, panel data are often used. However, there is a lack of panel data in many countries, the surveys are generally limited in terms of number of individuals and the period of time covered is often constrained, which is a problem for a life-cycle analysis in particular. Moreover, there can be a lack of representativeness of panel data over time. Indeed, these data can present a problem of non-response to certain questions and of attrition which limits a long term analysis. So, it is difficult to follow the same individual during a long period of time.

That is why the use of pseudo panel data can be a good alternative and is employed in this paper. Indeed, the pseudo-panel approach is a relatively new econometric method first introduced by Deaton (1985) which enables a longitudinal analysis without genuine panel data. He proposed to apply panel data method to independent repeated cross-sectional data. The advantage is that these data methods are often available and facilitates long term analysis.

The principle of pseudo panel is to group individuals or households into cohorts based on time-invariant variables such as year of birth and gender. The cohorts are constructed by computing the average value of the different variables of interest for the individuals included in each cohort. Contrary to panel data which follow the same individuals over time, we follow cohorts of individuals whose composition changes over time but who share fixed common characteristics. Each cohort is then assimilated to an individual and traced over time to form a panel data set.

Some precautions must be taken to create pseudo panel data. First, we do not compute the true means of the cohorts which usually correspond to the average computed on the whole population within a cohort. In each survey, there are only some individuals belonging to a cohort who are interviewed. Thus we only have an approximation of the population means which can be subject to measurement errors with confidence intervals depending on the size of the cohort and of its homogeneity. However, the empirical means calculated converge to the real values, so it is important to have a sufficiently large number of observations in each cohort to avoid a bias in the estimation. Verbeek and Nijman (1992, 1993) have shown that the bias is small from 100 observations by cohort. That's why many empirical works neglect the measurement errors in return of large enough cohorts. This will also be our approach in this research

Furthermore, attention has also to be paid to the homogeneity of the cohorts. To reduce the measurement errors, we increase the size of the cohort but at the expense of its homogeneity. Thus, there is an arbitrary bias-variance because with a fixed sample size if we raise the number of individuals in each cohort we reduce the number of cohorts and the inter-cohort variability because we include too different individuals within each cohort; and in reverse if we reduce the number of observations in each cohort the estimation will be less accurate. Verbeek and Nijman (1992, 1993) have shown that the bias can be important even if the number of individuals in each cohort is large, if the inter-temporal and inter-cohort variability is low in comparison with the measurement errors. So, the objective is to minimize the variability within a cohort and increase it between cohorts while having a large enough number of observations.

While the majority of empirical applications of pseudo panel define cohorts according to birth year, some works mix several variables. Weis and Axhausen (2009) create cohorts in grouping year of birth, gender and household location. Bernard et al. (2011) use household residential location and house size to study the household electricity consumption. Calvet and Marical (2011) build several cohorts in grouping year of birth with the diploma and year of birth with the socio-professional groups. However, households can change their residential location along their life cycle, and individuals might change their professional status as well (e.g. from active to retired).

Finally, a problem of heteroscedasticity can be present with pseudo panel data. Indeed, the number of observations in each cohort can be much differentiated and also for a same cohort overt time (because we do not interview the same individuals). Thus, it can be controlled by a specific weighting. Nevertheless, Gardes et al. (2005) creates a pseudo panel from a panel survey and find that pseudo panel estimates are often closed to those based on genuine panel data.

2.3. Pseudo panel in transport literature

Several works turn to pseudo panel data in the transport literature and the majority of these empirical applications are interested in automobile. Madre (1990) presents an age-cohort-period model in conjunction with demographic forecasts to model projections of car ownership and use. Dargay and Vythoulkas (1999) present a first application of the use of pseudo panel data with a dynamic econometric model (dynamic partial adjustment model). They use the UK Family Expenditure Surveys to study the relationship between car ownership and its determinants (income, car purchase and car running costs, public transport fares, socio-demographic characteristics). Dargay (2002) investigates the factors determining car ownership for households living in rural and urban areas. Using the same data, she shows that car ownership is far less sensitive to motoring costs for households living in rural areas than for their urban counterparts. Dargay (2001) also works with a dynamic model in adding the question of asymmetry in the relationship between income and car ownership. This study shows that the income elasticity is more important with a rise in income than for a decrease, so there is a less important adjustment to a falling income than to a rising one. This study also shows that income elasticity is not constant but declines with increasing car ownership. Finally, Dargay (2007) uses the same modelling approach with a car travel demand model.

Huang (2007) applies linear and discrete choice models to generate forecasts of car ownership in Great Britain. He suggests in particular to combine pseudo panel with the random utility model (random utility pseudo panel models (RUPPM)). Weis and Axhausen (2009) use the Swiss National Travel surveys to create pseudo panel data and estimate induced travel with a structural equations model. They show in particular the importance of generalised cost on car mobility. Calvet and Marical (2011) works on the relation between fuel price and the fuel consumption of households. The French Family Expenditure surveys are used to create pseudo panel data between 1985 and 2006. They find that the long term fuel price elasticity is between -0.6 and -0.7. A differentiation by levels of income and residential areas is also implemented.

Finally, we can mention the study of Tsai and Mulley (2014a) who apply a dynamic partial adjustment model to analyse the determinants of public transport demand as well as the short-run and long-run demand elasticities. For a more detailed literature review on pseudo panel in transport see Tsai et al. (2014b).

The empirical studies have showed that pseudo panel data can be used with different modelling approaches such as static or dynamic models, random utility models, and structural equations models.

However, in this study, we do not have chosen a dynamic linear partial adjustment model because the intervals of time between two surveys are too distant (between 7 and 10 years) to account for the temporal adjustment process of individuals.

3. Parisian context

Car ownership and use have reached a threshold in Paris region. Indeed, car ownership stagnates at around one car per household and car mobility has reached a maximum at 1.5 trips per person and per day. This led to a decrease of the modal share of car from 44% of trips in 2001 to 38% in 2010. However, this automobile ceiling has not appeared at the same time for the inhabitants of different zones, more or less distant from the city center. We note since 1990 a demotorisation (reduction of the percentage of household equipped in automobile) and a reduction of the average number of trips made by car by the inhabitants of the city of Paris. The same phenomenon has appeared in the inner suburbs in the 2000s. Finally, the rise in motorisation and use only continues in the outer suburbs today.

Some first results can be highlighted by distinguishing the cohorts over time. In figure 1, the horizontal axis represents the age of the household reference person and the number of cars per household is given on the vertical axis. The different lines represent the cohorts. In order to make reading easier, the figure is represented in using cohorts of 10-year bands. For each line, the first point comes from the first survey where the cohort is present with enough observations while the last point represents the last survey where the cohort is present. Some cohorts have less than five points because they are not present in each survey over time. This graphical representation allows us to express in a same figure the life-cycle effects and the generation effects.

If we are interested in the life-cycle effects, a global trend present in each cohort is noted. There is a growth of car ownership in the household until the household reference person reaches around 50-55 years old which corresponds to a maximum. Then, a progressive decrease of car ownership is observed.

Concerning the generation effects, older generations have a significantly lower level of car ownership and in particular for the oldest ones who have grown up before the automobile boom while the generations born from the 1950s tend to have a homogenous level of car ownership since the lines are closed.

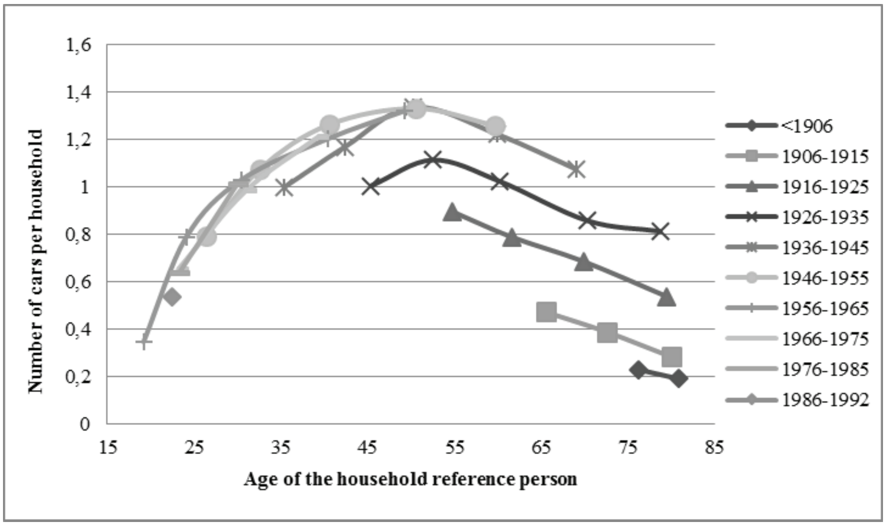

Fig 1. Car ownership by cohorts in Paris region from 1976 to 2010

Figure 2 points out car travel for different cohorts over time. The reading of the figure is the same as the previous one with the age of the household reference person on the horizontal axis and the number of trips per day made by car per household on the vertical axis. The life-cycle analysis shows a maximum of car travel around 40-45 years old. This maximum happens earlier than the maximum of car ownership.

For the generation effects, the older generations (born before WWII) make relatively fewer trips by car. For the newer generations, the effects are not similar to those for car ownership where a homogenous behaviour is present. For car use, a maximum of car travel seems to be reached by the 1946-1955 and 1956-65 generations while the younger ones (1966-1975, 1976-1985, 1986-1992) tend to use the automobile less. Some potential explanations will be given in section 5.

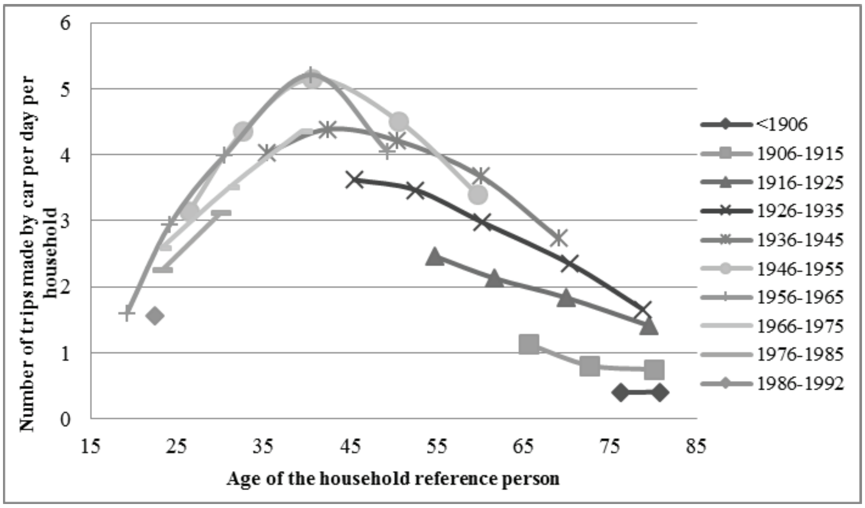

Fig 2. Car travel by cohorts in Paris region from 1976 to 2010

4. Data and model

4.1. Data

Our case study is the Paris metropolitan area which includes territories with contrasted densities and a differentiated access to public transport. We distinguish Paris, inner suburbs and outer suburbs. This differentiation enables to compare in particular a zone with an excellent public transport system (the City of Paris) and peripheral zone with an important car dependency (Outer suburbs).

Pseudo-panel data are constructed by using a succession of five large independent surveys (Enquête Globale Transport) conducted in 1976, 1983, 1991, 2001 and 2010 where between 8000 and 15000 households have been surveyed according to the different waves. In our case, cohorts have been constructed by grouping households according to the year of birth of their reference person using 3-year bands. The large majority of the cohorts have much more than 100 observations which helps to avoid measurement error problems. Socio-professional groups and level of education cannot be added to year of birth because this information is not available in each wave. Moreover, the analysis is conducted at household level and not at individual level because we have only access to the household income bracket. Finally, the area of residence is a time-variant variable, especially for a long period analysis so it has not been included for the cohorts. In terms of interpretation, using only year of birth as time-invariant variable allows us to interpret the coefficients as generation effects.

4.2. Model specification

The specification chosen is the semi-log model:

$$C_{c,t} = cst + \beta_Y Y_{c,t} + \beta_F F_t + \beta_A A_{c,t} + \beta_C K_{c,t} + \sum_{n=1}^{3} \beta_{Ln} L_{n,c,t} + \sum_{n=1}^{6} \beta_{AGEn} Age_{n,c,t} + \alpha_c + \varepsilon_{ct}$$

Where $c = 1, \dots, N, t = 1, \dots, T$ and the variables Y, A and K are estimated by its intra-cohort average. $C_{c,t}$ represents car ownership (number of cars per household) or car travel demand (number of trips per day made by car per household) according to the model estimated. $Y_{c,t}$ is the logarithm of household income expressed in 2013 euros in cohort c in period t, F_t is fuel price expressed in 2013 euros per litre taking into account the repartition between petrol and diesel in the car fleet. F_t is supposed to be the same for each household in period t. $A_{c,t}$ is the number of adults (18 years old and over) per household in cohort c in period t, $K_{c,t}$ is the number of children per household in cohort c in period t. $L_{n,c,t}$ are dummy variables representing the residential location of the household (Paris, inner suburbs, outer suburbs).

$Age_{n,c,t}$ are life-cycle dummy variables defined in 6 age bands:

$Age_{1ct} = 1$ if the age of the household reference person is under 25, 0 otherwise

$Age_{2ct} = 1$ if the age of the household reference person is between 25 and 34, 0 otherwise

$Age_{3ct} = 1$ if the age of the household reference person is between 35 and 44, 0 otherwise

$Age_{4ct} = 1$ if the age of the household reference person is between 45 and 54, 0 otherwise

$Age_{5ct} = 1$ if the age of the household reference person is between 55 and 64, 0 otherwise

$Age_{6ct} = 1$ if the age of the household reference person is 65 or over, 0 otherwise

α_c is a cohort-specific effect supposed to be constant in each cohort over time. As $Age_{n,c,t}$ are linearly dependent, the age band 35-44 has been dropped in the estimation ($\beta_{AGE3} = 0$) and is seen as the reference to analyse the life-cycle effect. It is the same for the residential location dummy variables $L_{n,c,t}$ where living in Paris is the reference and for the generation effects where the 1950-1952 is the reference. ε_{ct} is assumed to be a normal zero-mean error term and *cst* is the intercept term. For the representativeness of the cohorts, we have limited the analysis to households having a reference person between 18 and 85 years old.

Finally, in order to correct heteroscedasticity, all variables are weighted by the square root of the number of households in each cohort. To estimate the model, cohort-specific intercept terms have been included in the equation so it can be seen as least-square dummy variables (fixed-effects model) and be estimated by the OLS procedure. This method enables to have a consistent estimation. In our case, the cohort-specific intercept terms can be interpreted as generation effects.

5. Empirical results

5.1. Car ownership model

The car ownership model (table 1) has a very good fit (R-square close to 1) showing that it explains the data well. The number of adults in the household has a positive impact on the number of car held but having a child is not a significant determinant of car ownership in the model. The logarithm of constant income per household is positive and significant showing the positive and concave influence of income on car ownership. Moreover, fuel price is not significant which corroborates that buying a car is a long term process while the evolution of fuel price mainly influences car travel (short term adjustments) as shown in the car travel model estimation.

Table 1. Estimation results of the car ownership model

	Coefficient	Standard error	p-value
Intercept	-4,432	0,957	<,0001
ln (constant income)	0,485	0,095	<,0001
Fuel price	0,013	0,029	0,649
Number of adults	0,261	0,069	<,0001
Number of children	0,042	0,036	0,243
Inner suburbs	-0,173	0,277	0,536
Outer suburbs	0,212	0,196	0,283
Life-cycle effects			
under 25	-0,214	0,082	0,011
25-35	-0,106	0,033	0,002
45-55	0,086	0,036	0,020
55-65	0,150	0,053	0,007
65 and over	0,121	0,068	0,081
Generation effects			
<1905	-0,452	0,101	<,0001
1905-1907	-0,471	0,092	<,0001
1908-1910	-0,483	0,085	<,0001
1911-1913	-0,465	0,074	<,0001
1914-1916	-0,428	0,071	<,0001
1917-1919	-0,444	0,062	<,0001
1920-1922	-0,378	0,050	<,0001
1923-1925	-0,342	0,047	<,0001
1926-1928	-0,317	0,042	<,0001
1929-1931	-0,266	0,040	<,0001
1932-1934	-0,209	0,039	<,0001
1935-1937	-0,182	0,036	<,0001
1938-1940	-0,103	0,033	0,003
1941-1943	-0,113	0,032	0,001
1944-1946	-0,103	0,030	0,001
1947-1949	-0,072	0,027	0,011
1953-1955	-0,028	0,029	0,324
1956-1958	0,012	0,030	0,702
1959-1961	0,014	0,032	0,657
1962-1964	0,022	0,033	0,515
1965-1967	0,020	0,034	0,572
1968-1970	0,044	0,036	0,229
1971-1973	0,065	0,040	0,115
1974-1976	0,029	0,044	0,516
1977-1979	0,116	0,044	0,010
1980-1982	0,074	0,051	0,152
1983-1985	0,012	0,061	0,844
1986-1988	0,103	0,079	0,200
1989-1992	0,049	0,120	0,681
R^2	0,980		

Concerning the life-cycle effects, the model confirms a maximum of car ownership reached after 50 years old. Indeed, relative to the reference age band (35-44 years old), the coefficients estimated for under 25 and 25-35 are statistically negative so the impact of age is negative on car ownership for the 18-35 years old. Then, 45-55 and 55-65 is significantly positive so the maximum of car ownership is at the end of one's professional life, which correspond often to a maximum of salary in a professional career. However, we don't find a significant difference in car ownership after retirement.

Concerning the generation effects, a graphical representation is presented for car ownership and car travel in figure 3. The vertical axis represents the value of the cohort coefficients estimated in each model and the horizontal axis is the birth year of the cohorts. The value of the coefficients estimated for car ownership shows that all the years before 1950 have a significantly negative coefficient showing that being born before WWII has a negative impact on car ownership. For cohorts after 1950, the differences are not significant which express the converging car ownership behaviour of households in parallel with the democratisation of automobile. These coefficients confirm the representation in figure 1. We can mention that the generational gap has decreased over time.

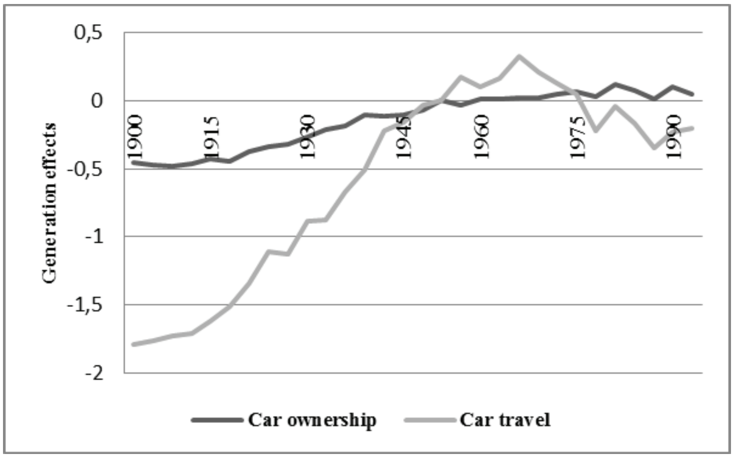

Fig 3. Generation effects for car ownership and car travel

5.2. Car travel model

As with the car ownership model, the car travel demand model (table 2) fits the data well. Contrary to the car ownership model, income is not significant while fuel price is. The coefficient estimated for fuel price is negative showing that the households adjust their trips in parallel to a rise in fuel price. The residential location has also an impact on trips made by car.

The coefficients are positive and significant for inner and outer suburbs, so the numbers of car trips made in Paris are lower than in peripheral area. In a dense area, it will be easier to reach destinations by non-motorised modes. Indeed, in Paris there is a good alternative to car use with an important public transport infrastructure supplemented by new forms of mobility (bike and electric car sharing services) and politics against automobile (bus lanes in Paris have induced a reduction of road space available for cars and a decrease in parking spaces) which favour alternative modes to automobile. In addition, the coefficients estimated display that the further away a household is from the city center the more a household uses automobile because the inhabitants in peripheral areas are car dependent.

The number of adults and children in the household positively influence the number of trips made by car. This is corroborated by the life-cycle effects. All the coefficients are negative so the maximum of car use is during the age band 35-44 (reference). It is often during this period of life that households are the most active in their professional life and have children dependent on their parent.

As for ownership, all the generation coefficients estimated in the car travel model are negative until the cohort

1947-1949 (figure 3) and the generational gap has decreased over time. Then, the coefficients express that the new generations tend to use car less than the cohorts of the 1960s. A trend of reduction in car use for the new generations emerges; however the differences are not statistically significant because of a lack of observations for new generations (one or two). This trend could be tested with an annual survey for instance.

Table 2. Estimation results of the car travel model

	Coefficient	Standard error	p-value
Intercept	-1,300	3,944	0,743
ln (constant income)	0,050	0,392	0,899
Fuel price	-0,632	0,121	<,0001
Number of adults	1,606	0,284	<,0001
Number of children	0,765	0,148	<,0001
Inner suburbs	2,180	1,142	0,061
Outer suburbs	3,020	0,807	<,0001
Life-cycle effects			
under 25	-0,627	0,339	0,069
25-35	-0,339	0,138	0,017
45-55	-0,456	0,148	0,003
55-65	-0,237	0,221	0,286
65 and over	-0,169	0,281	0,549
Generation effects			
<1905	-1,793	0,415	<,0001
1905-1907	-1,767	0,378	<,0001
1908-1910	-1,725	0,352	<,0001
1911-1913	-1,712	0,303	<,0001
1914-1916	-1,617	0,294	<,0001
1917-1919	-1,512	0,254	<,0001
1920-1922	-1,344	0,205	<,0001
1923-1925	-1,106	0,195	<,0001
1926-1928	-1,129	0,174	<,0001
1929-1931	-0,881	0,164	<,0001
1932-1934	-0,880	0,160	<,0001
1935-1937	-0,666	0,147	<,0001
1938-1940	-0,506	0,137	0,001
1941-1943	-0,224	0,133	0,098
1944-1946	-0,154	0,122	0,210
1947-1949	-0,035	0,113	0,754
1953-1955	0,178	0,118	0,136
1956-1958	0,103	0,124	0,412
1959-1961	0,165	0,130	0,211
1962-1964	0,323	0,135	0,020
1965-1967	0,209	0,142	0,145
1968-1970	0,127	0,149	0,400
1971-1973	0,044	0,167	0,793
1974-1976	-0,225	0,181	0,218
1977-1979	-0,046	0,181	0,801
1980-1982	-0,165	0,211	0,439
1983-1985	-0,351	0,254	0,171
1986-1988	-0,228	0,327	0,489
1989-1992	-0,203	0,494	0,682
R^2	0.982		

For the general models, the income elasticity on car ownership is 0.47 and the elasticity of fuel price on trips made by car is -0.22 (table 4). Thus, income has a positive impact on the number of car per household while fuel price has a negative impact on car use. This is consistent with the literature (see for instance Goodwin et al. (2004) for a review of elasticities of road traffic and fuel consumption with regards to price and income).

To estimate income and fuel price elasticities according to the residential area and the level of income, distinct estimations (not presented) have been realised on several sub-populations. To avoid having too few observations, cohorts of 5-year bands have been created in each sub-population. Low income corresponds to a household belonging to the first three deciles of income, middle class to the 4th, 5th 6th and 7th decile of income and high income to the last three deciles.

For the models with residential differentiation, the impact of income on car ownership is not significant in Paris while it is positive in inner and outer suburbs. Thus, income in high density territories seems not to be a determinant of car ownership because the alternative to automobile avoids allocating the rise in income on car purchase.

The elasticity of fuel price on car travel is negative and decreasing with the distance to the center. So there is an adjustment of car use in each area but stronger where the alternative to car is better.

For the models with income differentiation, the income elasticity on car ownership is strong (1.12) for low income household, lower for middle class (0.48) and not significant for rich households. Thus, we notice the decreasing influence of income on car ownership found with the logarithm of income variable in the general model. Finally, the income differentiation is not relevant for fuel car elasticity in the modelling.

Table 3. Income and fuel prices elasticities

	Car ownership	**car travel**
	income	**fuel price**
Global model	0,47	-0,22
Residential differentiation		
Paris	-	-0,62
Inner suburbs	0,42	-0,25
Outer suburbs	0,22	-0,18
Income differentiation		
Low income	1,12	-
middle class	0,48	-
high income	-	-

6. Conclusion

The pseudo panel approach is a flexible method for long term analysis and analysis of structural changes. The data are often available with a long period of time covered and a wide range of models are applicable. This research has allowed us to identify the different determinants of car ownership and use using longitudinal data in the Paris metropolitan area. In particular, we have taken into account the life-cycle and generation effects in the modelling. Concerning the life cycle effects, the maximum of car ownership is after 50 years of age while the maximum of car use is around 40 years. The older generations have a significantly lower car ownership and use level while the younger are closer. This is explained by the democratisation of access to automobile which has tend to homogenise car travel behaviour. However, the youngest generations tend to use the automobile less which suggest a structural break in trend which have to be confirmed with annual data.

Several elasticities have been estimated in the models. We find an elasticity of income on car ownership of 0.47. The influence of income on car ownership is decreasing with regards to a rise in income and is even not significant for high income households. Moreover, the income is not a determinant of car ownership in the most urbanised area while it is in car dependent area. Fuel price elasticity on car travel of -0.22 is found, and the elasticity is more important in dense territories where the households can more easily adapt their behaviour to change in fuel price because the alternative modes are developed. Further improvements to the model are possible. First, life-cycle and generations effects can be investigated using the models distinguishing residential areas and levels of income in order to question the differentiated reactions of individuals over time according different living conditions. Then, a dynamic specification could be tested but with other data better fitted, in particular with annual data, to question the temporal adjustment process because individuals take time to adapt their behaviour. Finally, with the same data (EGT), we will widen the analysis to other modes of transport in particular the public transport demand.

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